What are the best motor tasks to use and calibrate SensoriMotor Rhythm Neurofeedback and Brain-Computer Interfaces? A preliminary case study

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Scientific Abstract Title:

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What is the motivation of your study?

SensoriMotor Rhythm (SMR)-based Neurofeedback (NF) and Brain-Computer Interfaces (BCI) are among the most used ElectroEncephaloGraphy (EEG) NF/BCI systems. Indeed SMR-NF/BCI have proven very promising for numerous applications, including attention-deficit and stroke rehabilitation (Sitaram 2016, Ang 2015), performance optimization (Gruzelier 2014) and BCI-based assistive technologies and gaming (Lotte 2015). Despite these promises, such systems have low performance and many of their users are “non-responders” (Sitaram 2016, Lotte 2015). There is thus a need to understand the limitations of current SMR-NF/BCI and to improve them.

What is your hypothesis/goal?

Many SMR-NF/BCI systems use machine learning. They are typically calibrated on EEG signals collected while the users are performing Motor Imagery (MI), i.e., imagining limb movements (Ang 2015, Lotte 2015). Once calibrated, they also use MI as NF control strategy. However, for many first time users of SMR-NF/BCI, performing MI is new and difficult, and they may be unable to perform clear MI. Thus, using MI for calibration and/or NF control may result in suboptimal EEG features and corresponding real-time feedback. Therefore, we aim at elucidating whether MI tasks are the best motor tasks to use for calibration and control in SMR-NF/BCI.

To do so, we are collecting EEG signals (64 channels, Biosemi Active Two) from subjects (so far N=1 subject) instructed to perform four different motor tasks and a rest task, for multiple trials. In particular, subjects have to 1) execute real feet movements; 2) imagine feet movements (walking); 3) observe feet movements (walking), in a first person view and 4) observe feet movements while imagining them at the same time.

We analyze the collected EEG signals using machine learning. More precisely, we optimize Common Spatial Patterns (CSP) spatial filters to build four SMR-EEG features, and classify these features to distinguish a motor task from the rest task using a Linear Discriminant Analysis (LDA) classifier (Lotte 2015). We performed two such analyses. First, we optimize both the CSP and LDA on the data of each of the four motor tasks separately, to identify which task leads to the strongest SMR modulation.

Second, we optimize CSP filters on the data of each of the four motor tasks (separately) while optimizing the LDA on imagined movement data, to find out whether calibrating EEG features on other tasks leads to higher performance in detecting MI.

What were the results?

So far, we recorded 36 trials for each motor task from a single subject. Performance was assessed using 6-fold Cross Validation (CV) classification accuracy. The resulting CV accuracies (motor task VS rest task) were 93% for the executed movements, 52.8% for the imagined ones, 72.2% for the observed movements and 73.6% for the observed and imagined ones. Interestingly enough, optimizing CSP filters on EEG signals recorded during executed movements lead to an increased performance for classifying imagined movements, with a CV accuracy of 61.8%.

What is the significance of the study?

These are only results from a single subject. Experiments are ongoing and results from additional subjects will be presented at the conference. Nonetheless, this still suggests that other motor tasks than MI may lead to stronger SMR modulations, e.g., movement observation. It also suggests that, at least for our subject, calibrating SMR-EEG features (here CSP) on executed movements can lead to more efficient SMR-NF/BCI.

References:

Ang, K. K. & Guan, C., *"Brain--Computer Interface for Neurorehabilitation of Upper Limb After Stroke"*, Proceedings of the IEEE, IEEE, 2015, 103, 944-953

Gruzelier, J. H., "*EEG-neurofeedback for optimising performance. I: a review of cognitive and affective outcome in healthy participants*", Neuroscience & Biobehavioral Reviews, Elsevier, 2014, 44, 124-141

Lotte, F.; Bougrain, L. & Clerc, M., "*Electroencephalography (EEG)-based Brain-Computer Interfaces*", Wiley Encycl. Electric. Electro. Eng., 2015

Sitaram, R.; Ros, T.; Stoeckel, L.; Haller, S.; Scharnowski, F. et al, "*Closed-loop brain training: the science of neurofeedback*", Nature Reviews Neuroscience, 2016

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